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Surface Electromyography (sEMG)-based Thumb-tip Angle and Force Estimation Using Artificial Neural Network for Prosthetic Thumb

Shahrul Naim Sidek*, Nor Anija Jalaludin, Abu Ubaidah Shamsudin

Department of Mechatronics Engineering, International Islamic University Malaysia, P.O. Box 10, 50728, Kuala Lumpur, Malaysia

Abstract

Normally, humans were born with five fingers connected to each of the hands. These fingers have their own specific role that contributes to different hand functions. Among the five fingers, the thumb plays the most special function as an anchor to many of hand activities such as turning a key, gripping a ball and holding a spoon for eating. As a result, the lost of thumb due to traumatic accidents could be catastrophic as proper hand function will be severely limited. In order to solve this problem, a prosthetic thumb is developed to be worn in complementing the function of the rest of the fingers. In this work the relationship between the electromyogram (EMG) signals and thumb tip forces are investigated in order to develop a more natural controlled prosthetic thumb. The signals are measured from the thumb intrinsic muscles namely the Adductor Pollicis (AP), Flexor Pollicis Brevis (FPB), Abductor Pollicis Brevis (APB) and First Dorsal Interosseous (FDI). Meanwhile the thumb tip force is recorded by using the force sensor (FSR). The classification of the EMG signals based on different force and thumb configuration is performed by using Artificial Neural Network (ANN). A series of experiments have been conducted and preliminary results show the efficacy of ANN to classify the EMG signals.

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1. Introduction

The numbers of amputees are high and increasing every year as reported in [1]. This includes lower limb and upper limb amputation. Lower limb amputation is the lost of body parts from waist and below. While for the lost of body parts from shoulder and below are considered as upper limb amputation and this includes amputation of fingers and hand [2]. Every normal-born human have five fingers connected to each of the hands. Each of the finger digits has their own functions and thumb plays roles as an anchor in many hand functions due to its unique anatomy. In addition, only thumb offers a unique opposability function that allows object grasping [3]. According to clinicians, thumb is responsible for at least 50 percent of overall hand functions [4]. Therefore, research in developing a prosthetic thumb is needed in order to help the amputees to regain the complete hand functions so as to live efficiently.

In the hand-prosthesis research field, considerable efforts have been made to improve the performance of the artificial devices to be more naturally operated [5-7]. In [5], the researchers have used the surface EMG signal to control the force of German Aerospace Centre (DLR) prosthetic hand for more dexterous operation. While in [6], the researchers have done study on the surface EMG signals for controlling the individual finger of a prosthetic hand non-invasively. Besides that, in [7] the researchers have used the surface EMG signal for controlling the movement of robotic hand to perform regular hand

* Corresponding author. Tel.: +03-6196 4467
E-mail address: snaim@iium.edu.my

activities such as grasping and holding. Furthermore in [8-11] various techniques such as Artificial Neural Network (ANN), RQA, Genetic Algorithm (GA), Wavelet transform and Support Vector Machines (SVM) have been used to classify the EMG signals for better prosthetic function.

The movement of thumb is controlled by the central nervous system in the brain. The brain sends a signal to the motor neurons in the form of action potentials through the nervous system. Upon receiving the signal, the motor neurons stimulate several muscles fibers that are located inside the muscle and causing for muscle contraction [12]. The contraction of muscles then generates forces to move the thumb. During contraction, the activated muscle fibers generate electrical potential, Electromyogram (EMG) signals that can be measured non-invasively from the skin surface [13]. The amplitudes of these signals are small ranging from 0 to 10 mV peak-to-peak and the frequencies are between 5 to 500 Hz [14].

According to Park et al. [4], the precision of thumb function is closely related to knowledge of the muscle signals governing the operation of the thumb. In [6], the authors reported that for each individual finger, the related EMG signals can be used to control its movement. Besides that, different finger movement requires different amount of force and [5] investigated the contribution of EMG signal to a number of finger movements. Based on the above discussion, the EMG signals can be use to control the prosthetic thumb for more natural operations and force is required by the prosthetic thumb for proper object handling which can measured at the thumb-tip by using force sensor.

2. Experimental method

2.1 Muscle Selection

Human thumb is controlled by three joint and nine muscles. The joints are Carpometacarpal (CMC), Metacarpophalangeal (MCP) and Interphalangeal (IP) as shown in Fig. 1. The muscles can be divided into two groups, known as intrinsic muscles and extrinsic muscles. Intrinsic muscles are shorter muscles that are originated primarily in the human hand. Besides the longer muscles called extrinsic muscles are located inside human forearm [15]. Muscles in the intrinsic group are Adductor Pollicis (AP), First Dorsal Interosseous (FDI), Flexors Pollicis Brevis (FPB), Opponens Pollicis (OPP) and Abductors Pollicis Brevis (APB). While the Flexors Pollicis Longus (FPL), Abductors Pollicis Longus (APL), Extensors Pollicis Longus (EPL) and Extensors Pollicis Brevis (EPB) are in the extrinsic group. Among all the nine muscles, only AP, FPB, APB and DIO are chosen for collecting EMG signals, since these intrinsic muscles are located at the outermost layer [4], [16]. Besides considering the biological aspect, the selection of the muscles also made based on the Power Spectral Density (PSD) of each muscle. Whereby, this function shows the strength of signals from each muscle through describing the signals' power distribution in frequency domain [17].

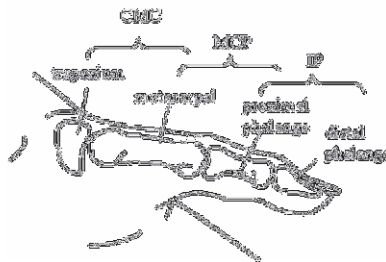


Fig. 1. Joints and bones of a thumb [3]

2.2 Experimental setup

The subject in the experiment was right-handed individual. She was instructed to place her thumb on the force sensor (FSR) that was secured on the angled block. The EMG signals from the intrinsic muscles were recorded by using G.tec DAQ with a sampling frequency of 1200 Hz. For the signals measurement purposes, the Ag/AgCl surface electrodes were placed above the related muscles as shown in Fig. 2a and Fig. 2b.

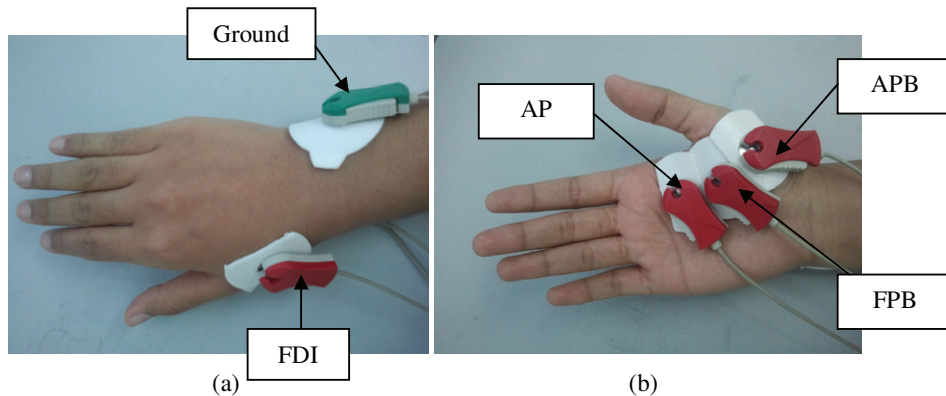


Fig.2. Placement for (a) Electrode on FDI muscle and (b) Electrodes on AP, APB and FPB muscles

During the experimental session, the subject was first instructed to press the FSR to the maximum value that the subject is capable of and the value is found to be around 25N. This is the Maximum Voluntary Contraction (MVC) value and the subject was asked to maintain the MVC force for 5 seconds. At the same time the subject exerts the thumb-tip isometric force, the EMG signals were recorded using the G.tec system. The experiment was repeated for four different thumb configurations which are at 0, 15, 30 and 45 degree of the angled block as shown in Fig. 3 and at four different thumb tip forces, which are 100% MVC, 75% MVC, 50% MVC and 25% MVC.

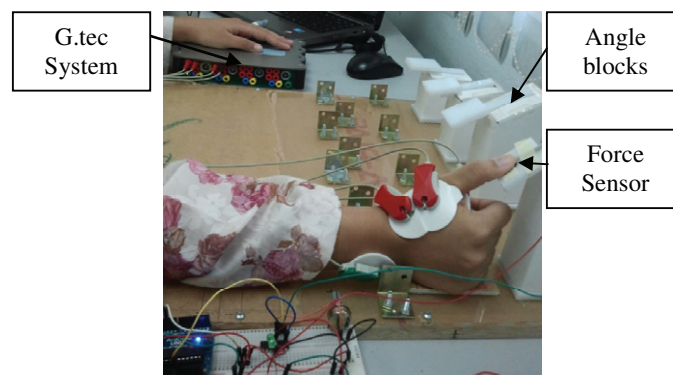


Fig.3. The experimental setup

2.3 Preprocessing of sEMG signal

The recorded EMG signal of the muscles can easily be contaminated by external interference such as electrode noise, motion artefacts, power line noise, ambient noise and inherent noise in surrounding electrical and electronic equipments. Therefore, in order to remove the noise, the recorded signals are filtered by using band pass filter with cut-off frequency between 20 to 500 Hz and also Notch filter with 50 Hz cut-off frequency [4], [17],[18], [19].

2.4 Feature extraction

The filtered data were then rectified by using full wave rectifier and transformed into Root Mean Square (RMS) values by using Eq. 1 to produce linear EMG signal,

$$RMS = \sqrt{\frac{\sum_{n=1}^N x_n^2}{N}} \quad (1)$$

where N is the number of EMG data, n is data index and x is value of the data

The signal is later smoothen by using the Moving Average (MA) using Eq. 2 to obtain the enveloped EMG signal as shown in Fig. 4.

$$MA = \frac{\sum_{i=1}^{i+(k-1)} x_i}{k} \quad (2)$$

where k is the size of the moving window, i is data index and x is the value of the data

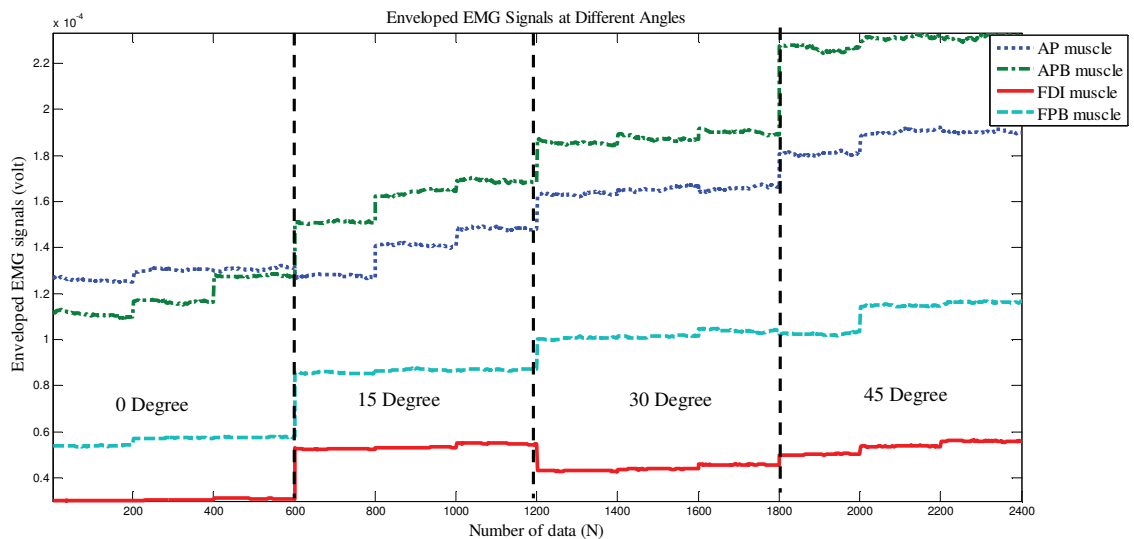


Fig.4. EMG signals of 25 % MVC force at 0, 15, 30 and 45 degree of thumb configuration

2.5 Classification of EMG signals by using ANN

The enveloped EMG signals of each muscle have unique pattern that can be used in signal classification. In this paper the goal is to classify the different force values at different block angles. As such, an artificial neural network (ANN) is deployed. The designed network consists of one input layer, one hidden layer and one output layer with sigmoid activation function.

In developing the network, the recorded signal was first divided into training data set and testing data set. The training datasets from four muscles, targeted forces and targeted angles that give the total of 2400 data sets were trained in the network (i.e. 600 input datasets from each muscle). The weights of the ANN were adjusted by using Levenberg-Marquart algorithm. To validate the network, 30% of input datasets was taken randomly and fed into the network and the outputs of the network were the estimated force of the thumb and the estimated angle of the thumb.

For the developed network, the choice of optimal number of hidden neurons used in the hidden layer is based on the evaluation of the ANN performance using Normalized Root Mean Square Error (NRMSE). The best ANN architecture shown by the smallest value of NRMSE or test error [20]. It should be noted that insufficient number of neurons could cause the network to unable to model the complex data resulting in poor fitting of the model. Meanwhile excessive neurons could cause the training time to become very long resulting in over fitting of the model from the data supplied. Therefore, a series of testing is performed by using various numbers of hidden neurons from 1 to 20 for evaluation and the result is shown in Fig.5. Based on the plot, the choice of 16 hidden nodes is selected to form the hidden layer of the ANN for the EMG signal classification due to the smallest test error for both outputs namely the force and the angle.

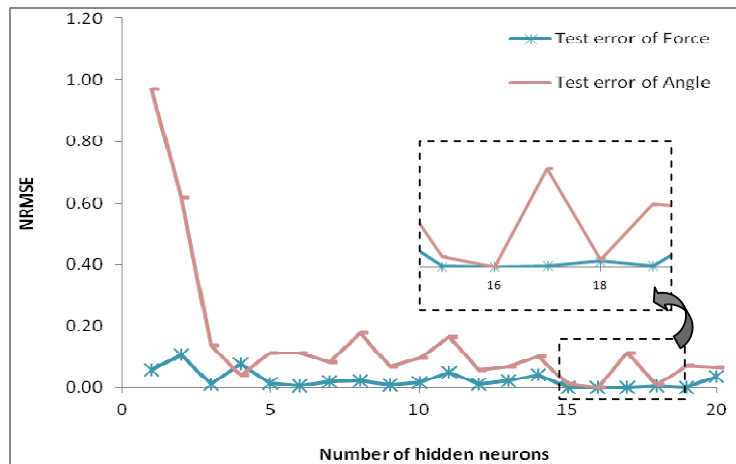


Fig.5. The ANN simulation result to determine the optimal number of hidden neurons

3. Results and Discussion

The performances of the ANN in capturing the relationship between the EMG signals and thumb-tip force at different thumb configuration are recorded in Table 1 in the form of Root Mean Square Error (RMSE) obtained from Eq. 3,

$$RMSE = \sqrt{\frac{\sum (x_i - y_i)^2}{N}} \quad (3)$$

where x , y and N indicate the measured force by the FSR, the estimated force from ANN and the total data, respectively.

The RMSE is calculated by determining the error between the actual values and the predicted values using the neural network. The small error obtained from the validation step reflected in Table 1 shows that the predicted values are very close to the actual values. But there are some errors that are slightly bigger compared to others due to the outliers in the predicted values as shown in Fig.6. However, only small portion of the predicted value are affected by the outliers, therefore it can be concluded that the ANN has successfully classified the EMG signal based on the desired output.

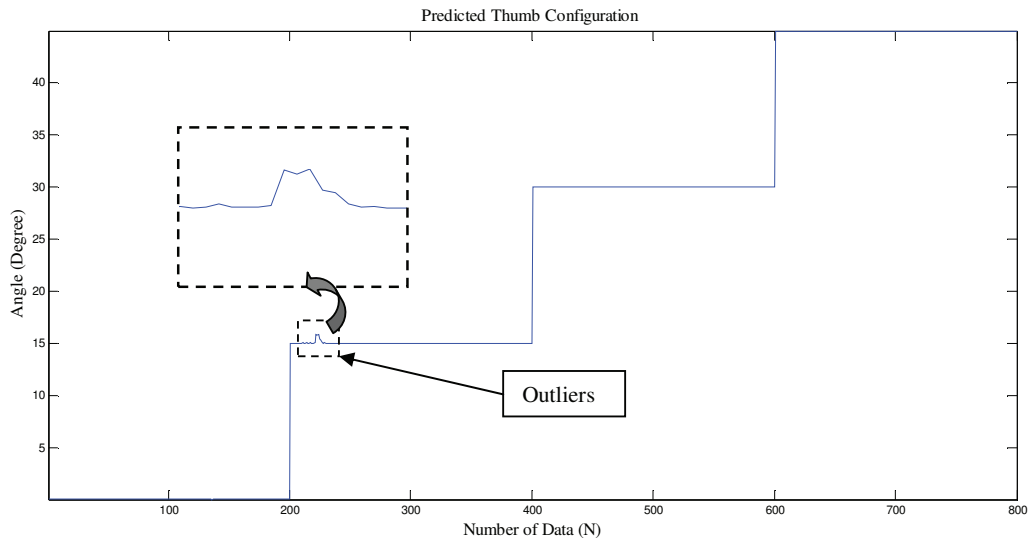


Fig.6. The predicted angles at 50% MVC

Table 1: The performance of force and angle estimation based on the error (RMSE) obtained from verification step.

Actual Force (%MVC)	Actual Angle (Degree)	Force Error (RMSE)	Angle Error (RMSE)
100	0	6.6668×10^{-8}	1.0085×10^{-8}
	15	1.3914×10^{-5}	1.1355×10^{-5}
	30	4.1380×10^{-7}	1.0897×10^{-6}
	45	2.8829×10^{-6}	2.2479×10^{-6}
75	0	2.6112×10^{-4}	1.6162×10^{-4}
	15	4.9644×10^{-6}	5.9614×10^{-6}
	30	9.2566×10^{-6}	5.1228×10^{-6}
	45	4.6268×10^{-6}	0.0699
50	0	6.1441×10^{-7}	8.8372×10^{-6}
	15	1.8041×10^{-5}	0.1105
	30	2.5787×10^{-5}	1.8555×10^{-6}
	45	1.4144×10^{-5}	2.1317×10^{-6}
25	0	1.2960×10^{-8}	1.5462×10^{-8}
	15	1.2527×10^{-5}	4.6403×10^{-6}
	30	0.0023	0.0027
	45	2.7511×10^{-5}	1.2256×10^{-5}

4. Conclusion

In this research work, the mapping between the signals from the AP, FPB, APB and FDI muscles to the thumb-tip forces under four different thumb configurations described by 0, 15, 30, 45 block degrees is established. The estimated force is obtained from 25%, 50%, 75% and 100% of the MVC. The selected muscles are the intrinsic type of muscle and directly involved in controlling the operation of the thumb. The result shows the efficacy of using the ANN model to classify the EMG signal for different value of force and thumb angle. This information is useful in developing a more natural control of prosthetics thumb.

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